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Estimation of net surface radiation using eddy flux tower data over a tropical mangrove forest of Sundarban, West Bengal

D. V. Mahalakshmi [1], *Arati Paul* [2], *D. Dutta* [2], *M. M. Ali* [1, 3], *V. K. Dadhwal* [1], *R. Suraj Reddy* [1], *C. S. Jha and J. R. Sharma* [1]

[1] National Remote Sensing Centre (NRSC), Balanagar, Hyderabad, India

[2] Regional Remote Sensing Centre-East (NRSC), ISRO, New Town, Kolkata, India

[3] Florida State University, Center for Ocean-Atmospheric Prediction Studies, USA

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In this study, net surface radiation (R_n) was estimated using artificial neural network (ANN) and Linear Model (LM). Then, estimated R_n with both the models (ANN and LM) were compared with measured R_n from eddy covariance (*EC*) flux tower. The routinely measured meteorological variables namely air temperature, relative humidity and wind velocity were used as input to the ANN and global solar radiation as input to the LM. All the input data are from the *EC* flux tower. Sensitivity analysis of ANN with all the meteorological variables is carried out by excluding one by one meteorological variable. The validation results demonstrated that, ANN and LM estimated R_n values were in good agreement with the measured values, with root mean square error (*RMSE*) varying between 21.63 W/m^2 and 34.94 W/m^2, mean absolute error (*MAE*) between 17.93 W/m^2 and 22.28 W/m^2 and coefficient of residual mass (*CRM*) between –0.007 and –0.04 respectively. Further we have computed modelling efficiency (0.97 for ANN and 0.99 for LM) and coefficient of determination (R^2 = 0.97 for ANN and 0.99 for LM) for both the models. Even though both the models could predict R_n successfully, ANN was better in terms of minimum number of routinely measured meteorological variables as input. The results of the ANN sensitivity analysis indicated that air temperatuere is the more important parameter followed by relative humidity, wind speed and wind direction.

Keywords: net surface radiation, artificial neural network, linear model, eddy flux tower

1. Introduction

Net surface radiation (R_n) has an important role in land surface (Li et al., 2009) and numerical weather prediction models and is defined as the difference between the incoming and outgoing radiation fluxes (short and long wave) at the earth's surface. It plays an important role in Earth's climate system as well as in transportation and exchange of fluxes between the land surface and atmosphere (Li et al., 1995; Xia et al., 2006). Hence, precise estimation of net surface radiation at regional and global scales is a vital input to many of the earth processes.

The net radiation balance at the earth's surface can be written in terms of four net radiation components as given in Eq. (1)

$$R_n = R_S\downarrow - R_S\uparrow + R_L\downarrow - R_L\uparrow \tag{1}$$

where $R_s\downarrow$ denotes the incoming shortwave radiation (W/m^2), $R_S\uparrow$ denotes the reflected shortwave radiation (W/m^2) and $R_L\downarrow$ and $R_L\uparrow$ are the incoming and outgoing longwave radiations (W/m^2), respectively. In general, number of radiation measurement sites were limited as compared to sites where meteorological observations (air temperature, humidity, wind velocity, etc.) are recorded regularly. There are several surface radiation observational networks for providing long-term radiation budget that includes Baseline Surface Radiation Network (BSRN) (Ohmura et al., 1998), the Surface Radiation Budget Network (SURFRAD) (Augustine et al., 2000), and the FLUXNET, a network of regional networks, station data. FLUXNET database (Baldocchi et al., 2001) is a global network of networks for micrometeorological measurements (~ 500 sites). It is well understood that the flux tower data are the best, but use is limited due to sparse network across the globe (Diak et al., 2000), especially in inaccessible areas. Besides, they are costly, they need frequent maintenance and calibration (Rahimikhoob, 2010). The measurement of solar radiation is more prone to errors and often encounters more problems such as technical failure and operation related problems than other meteorological data (Tang et al., 2010). Hence, there is a need to develop models to estimate net radiation or its parameters using minimum meteorological data. In literature, Artificial Neural Networks (ANN) has been widely used for estimating Global Solar Radiation (GSR) (Rumbayan and Nagasaka, 2012; Zhou et. al., 2005). Many conventional methods have been used by several authors as a function of meteorological variables in order to estimate GSR. Based on the mathematical forms, it can be classified as parametric (such as Angstrom-Prescott type methods) (Ertekin and Evrendilek, 2007) and non parametric (such as ANN based) (Fadare, 2009). ANN has shown its best efficiency tool to build the mathematical relationship using different input parameters (Wong and Chow, 2001) which have no specific relationship. Hence, there are several studies to estimate GSR using the ANN approach in many locations. For example, Al-Naimi et al. (2014) and Jiang (2008) showed that the ANN has the ability to produce accurate estimates of monthly mean daily global solar radiation using limited meteorological data. Further, Sözen et al. (2004) used ANN approach for estimating the spatial GSR maps over Turkey. As it is non-linear and requires no prior assumption concerning the data relationship, ANN becomes a useful tool for predicting solar irradiation.

Literature survey reveals that there limited studies are available in estimating the net radiation using ANN and meteorological data (Ferreira et al., 2011). In the present study, ANN and LM techniques were used to estimate net surface radiation using meteorological data for application in earth processes.

2. Materials and methods

2.1. Study area

The study area is located in a Sundarban mangrove forest (mean canopy height of 5 m) in Indian region and is given in Fig. 1 where the black circle indicates location of the Eddy flux tower of 15 m height at Bonnie camp. It is the

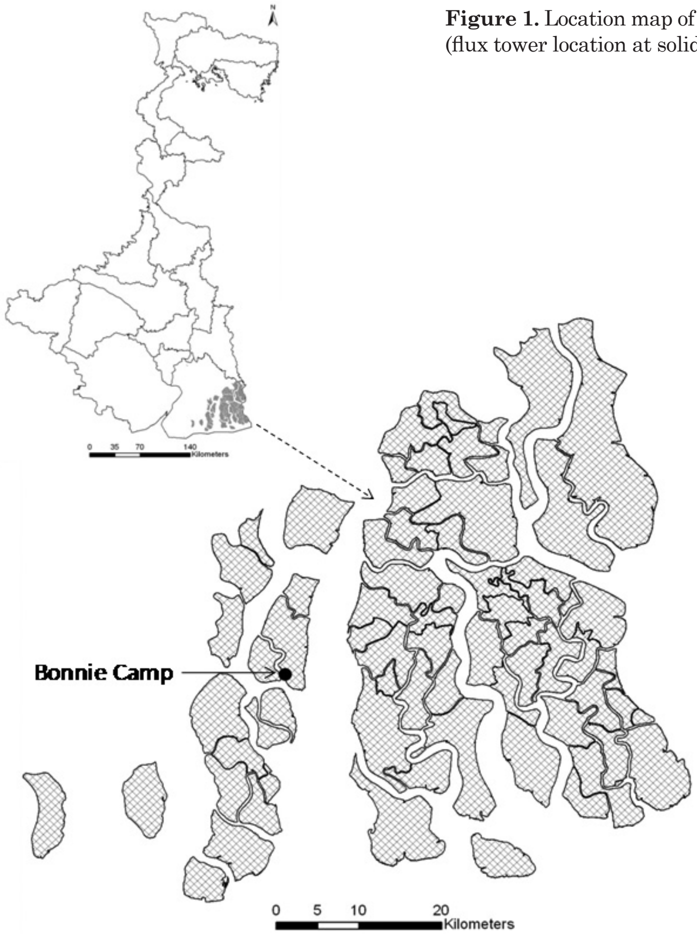

Figure 1. Location map of the study area (flux tower location at solid black circle).

largest continuous stretch of mangrove forest of the world delimited by 21° 40’ 04” to 22° 09’ 21” N latitudes and 88° 01’ 56” to 89° 06’ 01” E longitudes covering an area of 9 630 km^2 in the Indian region. It is the largest delta in the world, situated between Bangladesh and India formed by the distributaries of Ganga and Brahmaputra river (Seidensticker and Hai, 1983; Papa et al., 2010). The landscape is characterised by a web of tidal water systems with very high relative humidity (RH) between 70–88%. The mean maximum temperature of 34 °C in June (monsoon season) and the mean minimum temperature of 11 °C in January (winter season) was observed (Mukhopadhyay et al., 2006; Suraj et al., 2016) for the period of one year (April 2012 to March 2013). This region is experiencing occasional rains throughout most of the years, barring January and February (Chaudhuri and Chouddhury, 1994), and the monsoon season (June-September) accounts for about 80% of annual precipitation (Suraj et al., 2016). The deltaic Sundarban is prone to periodic storm surges during pre and post monsoon seasons, causing land degradation and poses livelihood challenges.

2.2. In situ data

Eddy Covariance Flux Tower (15 m height) observations of meteorological variables (April 2012 to March 2013), net surface radiation (R_n) and global solar radiation ($R_S\downarrow$) data (November, 2012 to January, 2013) were used in the present study. More details about the sensors installed in flux tower at various levels, software used and data processing steps can be found in Suraj et al., 2016. Overall, the collocated dataset is composed of 13 248 samples with 10 minutes temporal sampling frequency. The meteorological data used in this study include air temperature (HMP45C-l; Campbell Scientific), relative humidity (HMP45C-l; Campbell Scientific), wind speed and direction (Wind Monitor 05103, RM Young, USA) at 2 m, 4 m and 8 m levels respectively. Besides, R_n (Kipp & Zonen CNR 4; Bohemia, NY, USA) was also used as predictor in ANN and for comparison. The total collocated dataset was normalized and partitioned into training (70%), validation (15%), and testing (15%) considering day, night and different months and is carried out as part of the National Carbon Project initiated by the Indian Space Research Organization. The footprint of the eddy-covariance flux tower (height of 15 m) is estimated to be about 200 m.

2.3. Methods

2.3.1. Linear models

For linear regression analysis most commonly used equation (Kjaersgaard et al., 2007) to estimate net radiation at the surface is

$$R_n = a \cdot R_s\downarrow + b \tag{2}$$

where a and b are regression coefficients, $R_s\downarrow$ is the downward shortwave radiation, commonly measured variable compared to R_n (Gilgen and Ohmura, 1999; Wild et al., 2005). It can also be obtained from satellite observations (*e.g.*, Li et al., 1993; Liang et al., 2006, 2007). This method is useful when global solar radiation data is available. Moreover, long term global solar radiation at surface enables us to depend on linear models. Considering the $R_S\downarrow$ data, measured in the Eddy Flux Tower, in the LM training Phase, seventy percent (70%) of data set (see Item 2.2.), was used to calculate the regression coefficients of Eq. (2) for LM model and is shown in Fig. 2. The data points are very close to liner fit. The regression coefficients (a and b) were 0.818 and –48.14, respectively, which were used for estimating the R_n using Eq. (2) for the rest of the data.

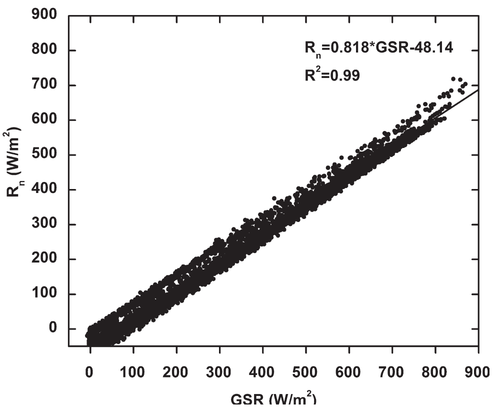

Figure 2. Scatter between global solar radiation and R_n from eddy flux tower data.

2.3.2. Artificial neural network (ANN)

Generally ANN contains three layers, *e.g.* input layer, hidden layers, and an output layer (Caner et al., 2011). It has ability to train input data using input-output relationship based on their connections in order to provide desired function. It can estimate the output for unknown datasets (Bocco et al., 2010) with existing function. Three steps are followed while developing ANN Model i) selection of input and target data to the network along with network parameters, ii) training of the network to estimate the output and iii) testing step for validating output data with input data, which are not used in developing the model. Further details about it can be found in Caner et al. (2011). The performance of the model has been evaluated using statistical error estimates such as Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*) and R^2 (Caner et al., 2011; Ferreira et al., 2011). Further, we have also accessed the performance based on coefficient of residual mass (*CRM*) and modelling efficiency (*ME)*. More details about *CRM* and *ME* can be found in Bandyopadhyay et al.

(2008). *CRM* indicates overall underestimation or over estimation. For example, *CRM* would be zero for perfect estimation, positive and negative for under- and over- estimations respectively. The value of *ME* would be 1.0 when all the estimated values match perfectly with the observed ones. Whereas negative values and values close to zero indicates poor performance of the estimation method.

3. Results and validation

Net surface radiation (R_n) is obtained using the LM model with GSR ($R_S\downarrow$) as input. Further, we have also estimated R_n from the ANN using the Marquardt-Levenberg algorithm as it was found to be best suited training algorithm (Lubna et al., 2013; Luenberger and Ye, 2008). The meteorological data include ambient mean air temperature, relative humidity (*RH*) and wind speed (*WS*) as well as wind direction (*WD*) at 2 m, 4 m and 8 m respectively from April, 2012 to March, 2013. In this case, we used all meteorological parameters (November, 2012 to January, 2013) as input to the model. The rest of the ANN model is used to study the input layer data influence on output as discussed in the later part. Estimation of $R_s\downarrow$ has been made using ANN and meteorological data and has validated extensively over different locations (Al-Naimi et al., 2014; Jiang, 2008; Qin et al., 2011). Limited studies are available for estimation of R_n using ANN technique. In earlier studies by Ferreira et al. (2011), estimated R_n using meteorological data along with soil moisture and soil temperature. But in the present study only routinely available meteorological variables have been used for estimating R_n (see Tab. 1). Both *CRM* and *LM* are negative for ANN indicating over estimation of modelled data.

Modelled R_n from ANN and LM methods were compared with observed data based on correlation coefficients. The comparison between the observed and the ANN model is shown in Tab. 1 and Fig. 3a with *RMSE* of 33.94 W/m^2 and correlation coefficient of 0.97. It can be noted from Tab. 1 that both the models have low *RMSE* and significantly high correlation coefficient. In the present study ANN could estimate net radiation using minimum meteorological parameters (Tab. 1). The results obtained are consistent with Ferreira et al. (2011) with different meteorological and soil parameters as input.

Further, the comparison between R_n observed and that obtained from a linear model (LM) is given in Fig. 3b with RMSE and R^2 of 21.63 W/m^2 and 0.99. The data points are aligned closely along the regression line in comparison to Fig. 3a. The reason could be R_n is estimated from GSR, which is dependent variable. The results, shown in Fig. 3b, demonstrate that Eq. (2) estimates daytime R_n accurately with very high correlation coefficient ($R^2 = 0.99$) between measured and estimated values. This suggests that Eq. (2) is capable of monitoring long-term change in R_n accurately. However, LM is an empirical regression model

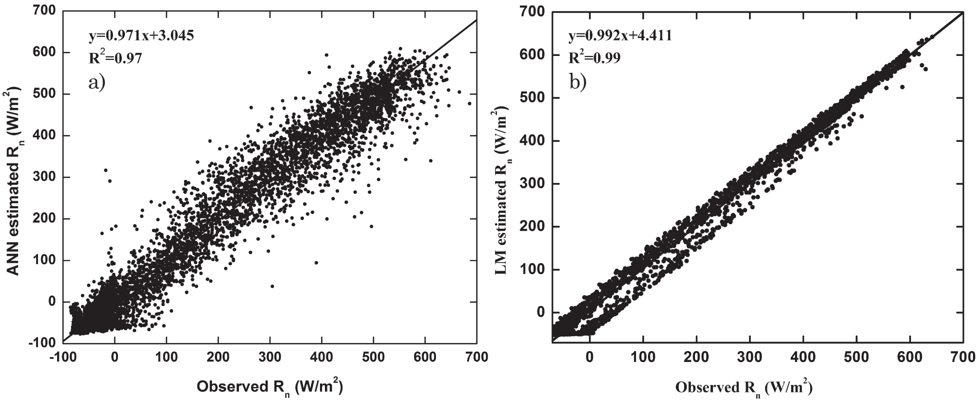

Figure 3. Scatter between observed and estimated R_n (*a*) ANN based (*b*) LM based models.

where the regression coefficients often vary with locations leading to large uncertainties at the site where measured data are not available to calculate coefficients (Chen et al., 2006). LM uses GSR as input, which is available only during daytime and hence, R_n estimation using LM is not possible during the night. In the present study instead of computing or measuring long wave radiation components separately, we estimate R_n directly. The value of *ME* also corroborates the methods used in the study.

The diurnal cycle of net radiations for cloudy days and a clear sky day were shown in Figs. 4a and 4b. ANN and LM model derived net radiation results matched well with observations during cloudy days and clear sky day. The time of occurrence of the peaks of the net radiation for the cloudy (14th November, 2012) and clear sky (1st November, 2012) days under consideration staggered

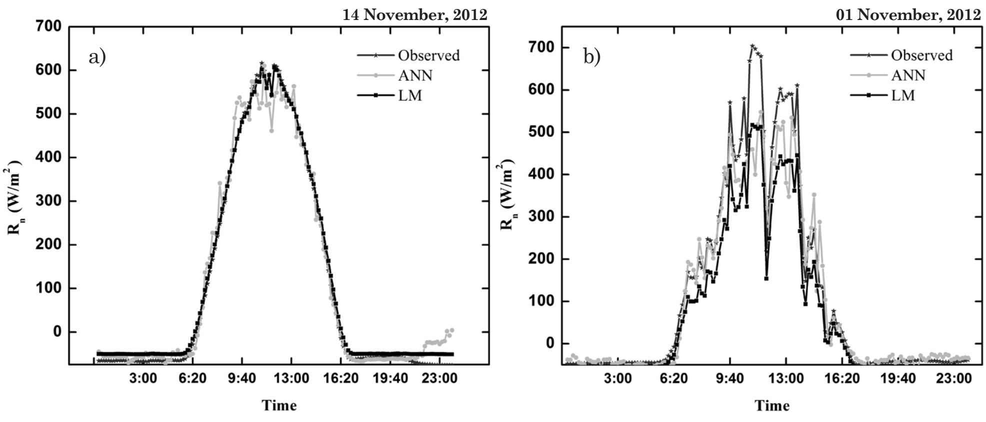

Figure 4. Observed and estimated diurnal circle of R_n from ANN and LM for (*a*) clear sky day (November 14, 2012) and (*b*) cloudy day (November 01, 2012).

between 12:00 hour and 14:00 hour (Fig. 4). The diurnal cycle of net radiation for cloudy days and clear day differs due to downward components of R_n that are controlled by cloud amount among other parameters (Brutsaert, 1975). This can be clearly seen in Figs. 4a and 4b.

The daily variations in net radiation can be seen in Figs. 5a–c. The result shows that ANN based estimates matched well with observations irrespective of clear or cloudy day. Further, it shows consistency during winter (study period) season due to little variations between months. The maximum value of R_n (718.48 W/m^2) was recorded on 6th November, 2012. In the months of December and January the R_n values were 622.47 and 641.8 W/m^2 respectively.

R_n estimated using all meteorological parameters and ANN (here after ANN-all) was considered as standard which was addressed earlier. Further, we used different input layers by omitting one parameter each time from the inputs, in order to understand its influence on output. Hence, four different groups of inputs have been prepared, eliminating each of air temperature or relative humidity or wind speed or wind direction at a time. Subsequently R_n has been estimated using these inputs in four different ANN models, keeping all model parameter same except input. The corresponding models hereafter will be represented as ANN1, ANN2, ANN3 and ANN4 respectively. Figure 6 (a–d) shows the scatter plots between observed and estimated R_n using ANN1, ANN2, ANN3 and ANN4 respectively, and corresponding statistical results were given in Tab. 1.

Table 1. Correlation and error estimates between observed and estimated R_n using different models.

Regression models	Parameter excluded	*RMSE*	*MAE*	*CRM*	R^2	*ME*
LM	–	21.63	17.93	–0.040	0.99	0.99
ANN1	Air temperature	66.08	42.93	0.014	0.89	0.91
ANN2	Relative humidity	40.09	26.51	–0.002	0.96	0.97
ANN3	Wind speed	42.73	26.74	–0.002	0.95	0.96
ANN4	Wind direction	33.92	21.35	–0.015	0.97	0.97
ANN-all	–	34.94	22.28	–0.007	0.97	0.97

Note: *RMSE*, *MAE* and *CRM* are in units of W/m^2.

Performance of ANN1 was poor in comparison to other ANNs. While, comparing performance of ANN1 to ANN4 with ANN-all it was found that air temperature is one of the important determining parameters followed by *RH* and *WS*. The correlation coefficients and *RMSE* have varied from 0.89 to 0.99 and 33.92 W/m^2 to 66.08 W/m^2 for ANN1 to ANN4 respectively (Tab. 1). The results show that the ANN-all and ANN4 models have the lowest *RMSE* and highest

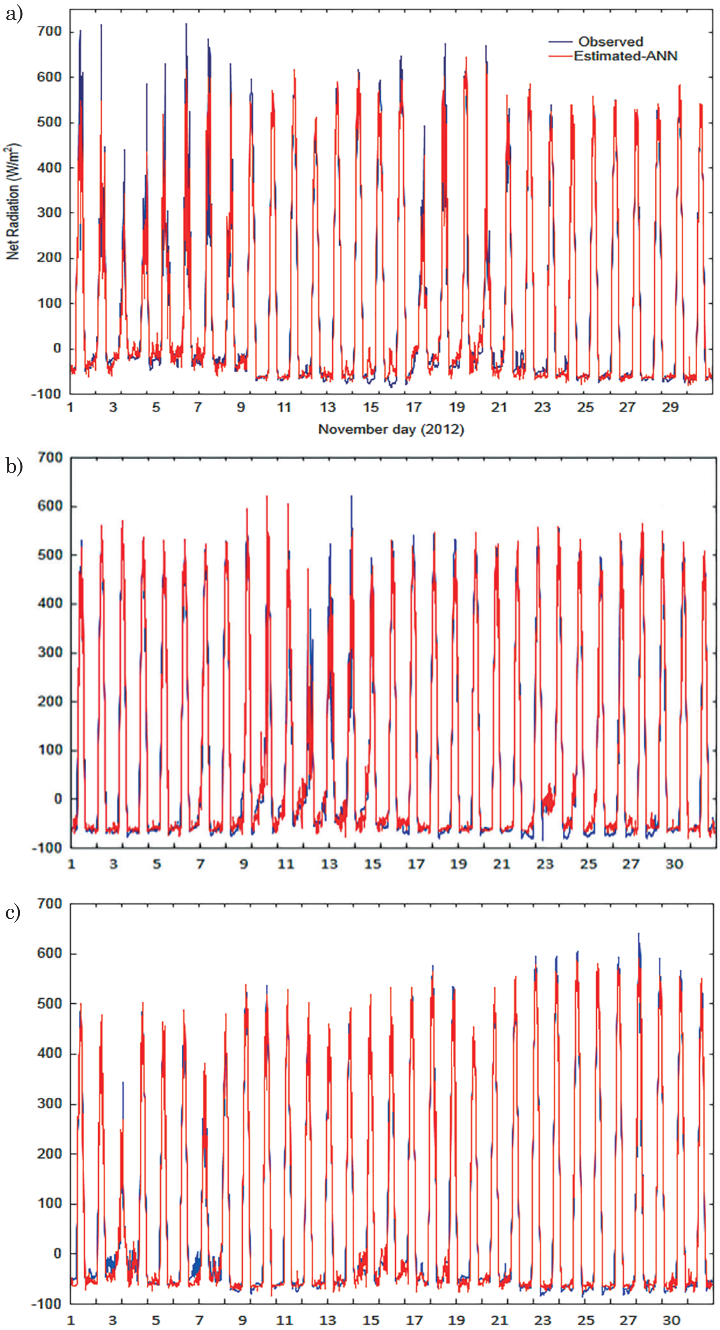

Figure 5. Ten-minutes R_n observed and estimated by ANN for: (*a*) November, 2012 (*b*) December, 2012 and (*c*) January, 2013.

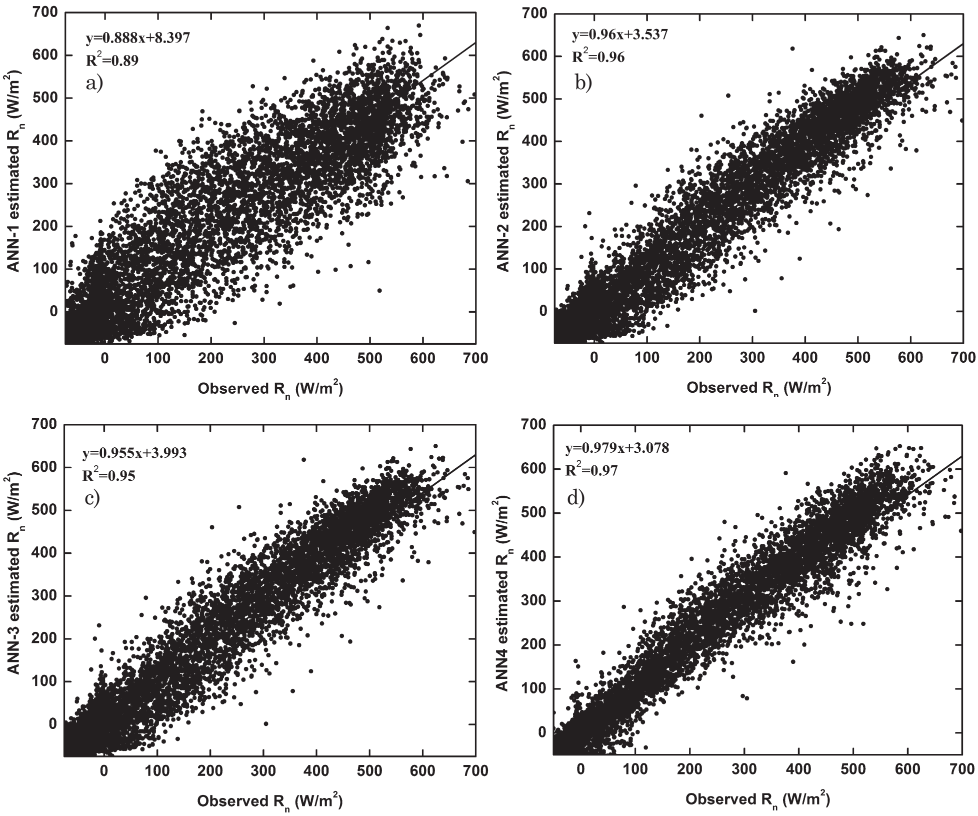

Figure 6. Scatterplot between measured and estimated R_n by: (*a*) ANN1, (*b*) ANN2, (*c*) ANN3 and (*d*) ANN4.

correlation coefficients (Tab. 1 and Fig. 6). The results also revealed that wind directions do not have significant contribution in estimating R_n while using ANN.

4. Conclusions

Net Surface Radiation can be estimated with high accuracy using simple meteorological variables using linear models and Artificial Neural Network model. The *RMSE* value in LM is very low followed by ANN4 and ANN-all. Even though both the models performed well, ANN has the ability to estimate R_n by using routinely available meteorological data with minimum parameters. Among different meteorological parameters air temperature was a key variable as input to ANN model. Out of all the meteorological variables wind direction had least contribution towards the estimation of R_n. Hence ANN with routine meteorological data is extremely useful for estimation of R_n where radiation data is not available.

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SAŽETAK

Procjena prizemnog neto Sunčevog zračenja iz podataka s tornja za mjerenje turbuletnih tokova iznad tropske šume mangrova u Sundarbanu, Zapadni Bengal

D. V. Mahalakshmi, Arati Paul, D. Dutta, M. M. Ali, V. K. Dadhwal, R. Suraj Reddy, C. S. Jha i J. R. Sharma

U ovom je istraživanju pomoću umjetnih neuronskih mreža (ANN) i linearnog modela (LM) procijenjeno prizemno neto Sunčevo zračenje (R_n). Potom su tako procjenjeni R_n iz oba modela (ANN i LM) uspoređeni s onima izmjerenim na tornju za mjerenje kovarijance turbuluentnih tokova (*EC*). Kao ulazni podaci u ANN korišteni su rutinski mjerene meteorološke varijable (temperatura zraka, relativna vlaga i brzina vjetra), a za LM globalno Sunčevo zračenje, koji su dobiveni na meteorološkom tornju za mjerenje turbulentnih tokova. Uslijedila je analiza osjetljivosti ANN s uključenim svim meteorološkim varijablama te su testirani ANN iz kojih su isključeni jedna po jedna meteorološka varijabla. Rezultati validacije pokazuju da se R_n procjenjeni pomoću ANN i LM dobro slažu s izmjerenim vrijednostima, pri čemu korijen srednje kvadratne pogreške (*RMSE*) varira između 21,63 W/m^2 i 34,94 W/m^2, srednja apsolutna pogreška (*MAE*) između 17,93 W/m^2 i 22,28 W/m^2, a koeficijent preostale mase (*CRM*) između –0,007 i –0,04 respektivno. Nadalje smo izračunali učinkovitost modeliranja (0,97 za ANN i 0,99 za LM) i koeficijente korelacije (R^2 = 0,97 za ANN i 0,99 za LM). Iako su oba modela mogla uspješno predvidjeti R_n, ANN je bio bolji u smislu korištenja minimalnog broja rutinski izmjerenih meteoroloških varijabli kao ulaza. Rezultati analize osjetljivosti ANN pokazali su da je temperatura zraka najvažniji ulazni parametar, koju slijede relativna vlažnost te brzina i smjer vjetra.

Ključne riječi: neto Sunčevo zračenje pri tlu, umjetna neuronska mreža (ANN), linearni model (LM), toranj za mjerenje turbulentnih tokova

Corresponding author's address: Dr. D. V. Mahalakshmi, Atmospheric & Climate Sciences Group, National Remote Sensing Centre, ISRO, Government of India, Balanagar, Hyderabad, India; tel: +91 858 3069 960; e-mail: mahameteorology@gmail.com